The next level of motor control: inspiration from the cerebellum

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Introduction

Animals are very good at moving around in and exploring unstructured, complex environments, a task still very difficult for modern robots. Therefore we may gain advantages by emulating biological nervous structures and algorithms used for sensory-motor control. In vertebrate animals, motor control is effected by the central nervous system, including forebrain, cerebellum, brainstem, and spinal cord, and many types of sensors for feedback (Fig. 1).

Current research in legged robots has been inspired by the control algorithms found in walking insects, which have similarities to the peripheral control circuits built into the legs and spinal cord of vertebrate animals. For example, both have central pattern generators (CPGs) – groups of coupled, oscillating neurons that drive walking gaits. Other low-level reflexes being designed in legged robots range from muscle stretch reflexes and spinal motor neuron reflex arcs, to substrate-finding leg reflexes and balancing reflexes.

These basic functions can be viewed as part of the bottom level of motor control in a hierarchical framework for behavior generation (Albus 1991). The next level of control would be to coordinate the low level reflexes and CPGs with higher level, voluntary behavioral controls. This level would also include the coordination of multiple elemental motor movements to achieve smooth, dynamically efficient trajectories.

In higher animals, these functions may occur at the level of the cerebellum. The cerebellum monitors both the motor commands descending from higher levels (motor areas of neocortex), and sensory feedback ascending from the periphery. Several current theories suggest that this neural structure learns an implicit "world model" with which to predict future states and modulate the motor output appropriately.

We have begun a research effort to design neural networks that emulate the cerebellum, and that are capable of both sensory prediction for adaptive filtering, and learning to monitor and help coordinate complicated motor sequences. These functions should prove very useful for sensory-motor processing in general, and in particular, for the operation of remote, autonomous spacecraft and planetary explorers.

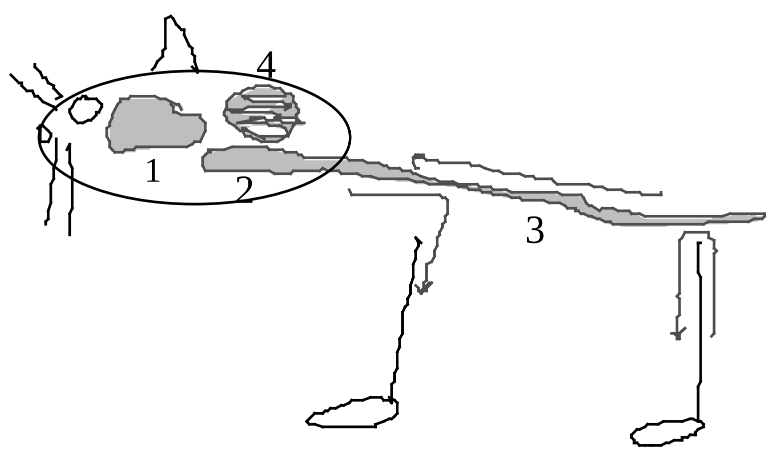


Figure 1

1. Cerebral cortex: motor planning

2. Brainstem nuclei: motor command relays

3. Spinal cord: command path, CPGs, reflexes, sensory feedback

4. Cerebellum: sensory-motor coordination

Review of cerebellar function and architecture

Traditionally, the cerebellum was thought to be a center for motor control, either running motor sequences autonomously (i.e., without having to think or engaging the neocortex), or regulating complex, multijointed motor tasks (Brooks 1986). Today, from control theory, we know that fine and fast motor control requires fast and accurate sensory and proprioceptive feedback to monitor the results of movements, especially for system dynamics where forces must be considered. One active area of research is feedforward control using internal predictive models and state estimation of the motor apparatus and sensory input (Fig. 2). The search for biological inspiration is just beginning to target the cerebellum (Miall and Wolpert 1996). Neurophysiological experiments have shown that cerebellar-like neural structures are involved in a wide variety of related functions, including motor coordination, conditioned reflexes, eye movements such as the vestibulo-ocular reflex, the generation of predictions for adaptive sensory processing, and even attentional gating and other more "cognitive" functions.

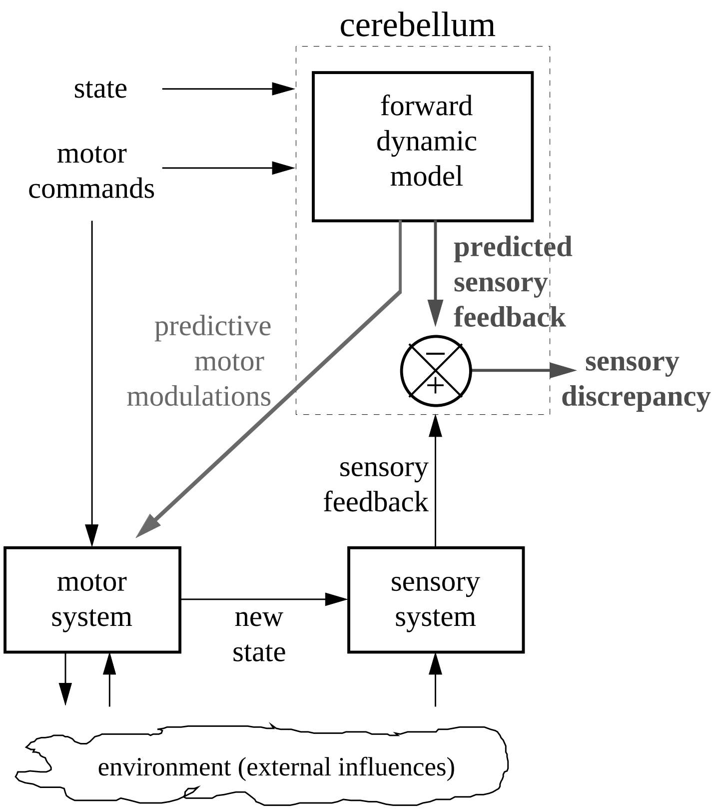


Figure 2. Predictive sensory-motor control schematic.

The cerebellum arose early in the evolution of vertebrate animals, and its basic architecture has been preserved and conserved across all vertebrate animals, including walkers, swimmers and flyers. Its cortex has three distinct cell layers (Fig. 3): an input layer containing billions of small granule cells, a layer of large Purkinje cell bodies, and a molecular layer that carries hundreds of thousands of parallel fiber axons through the large, planar dendritic tree of each Purkinje cell. The circuitry is comprised of 5 cell types arranged in repeating subunits, and is described as crystalline in its regularity. Purkinje cells provide the sole output of the cortex, projecting to several deep cerebellar nucleii, which then branch to further destinations.

This unique architecture provides the cerebellum several important advantages over other neural architectures for the control of high dimensional (or high DOF) systems. Its processing power lies in massively parallel computing: (1) there is a huge convergence of inputs, including sensory inputs from highly parallel and redundant (and often cheap and noisy) sensor arrays, internal state variables from the entire body, and motor commands descending from neocortex; (2) the granule cell layer has more cells than any other brain area, for decoding of states; and (3) massive connectivity is made possible by an efficient, densely packed, 3-d wiring scheme. This circuitry is also adaptive – there is synaptic plasticity in the molecular layer for learning correlations between inputs. This capability may allow the cerebellum to learn and update implicit models of the animal's body and environment, a function critical for state estimation. There are associative memory network models that map well onto the cerebellar circuitry, starting with David Marr's cerebellar theory published in 1969. For example, in 1988 Pentti Kanerva developed the Sparse Distributed Memory, a similar associative network which can learn patterns and sequences in its inputs. Kanerva's model has since been expanded and improved upon (e.g., see Sjödin et al. 1997).

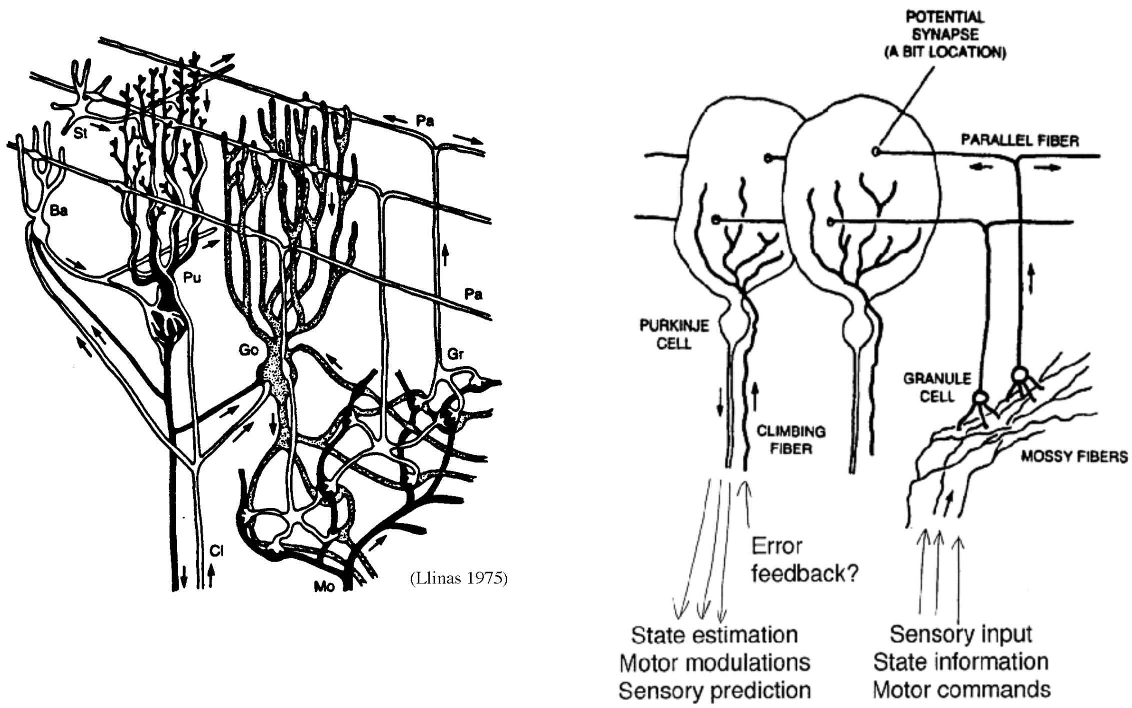


Figure 3 The basic cerebellar cortex microcircuit. **Left:** The five cell types and their connectivity. **Right:** Functional circuitry for associative memory. (adapted from Kanerva 1988)

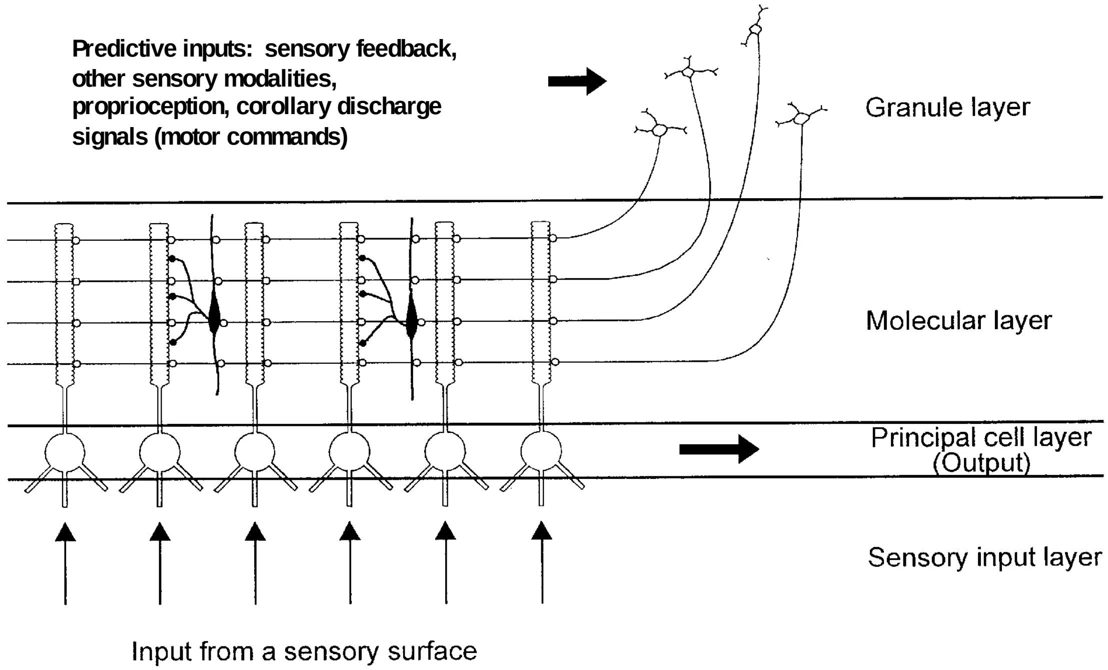


Figure 4 Simplified network schematic of a cerebellar-like adaptive filter found in electric fish. The circuit acts as an associative memory to predict the expected electrosensory input, andthen subtracts the prediction from the incoming sensory data. This compresses the sensory stream and amplifies novel, unexpected inputs. (from Bell et al. 1997)

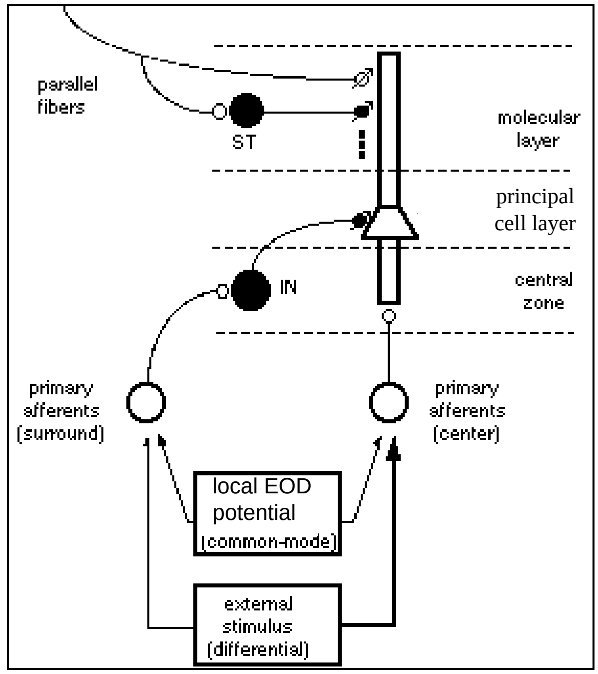
Research direction: building an artificial cerebellum

More basic research is still needed to fully understand the cerebellum, and there are several theories yet competing to explain its operation in detail (Bell et al. 1996). However, with today's technology we have enough knowledge and appropriate tools to begin simulating the hypothesized cerebellar functions, and then to design working networks in massively parallel, low power, analog VLSI. We are now running simulations to model the basic circuitry of the cerebellum at a functional level (Figs. 4,5). The initial simplified model is based on a cerebellar-like circuit in the electrosensory lobe of electric fish, which performs adaptive filtering through sensory prediction (Bell et al. 1997; Nelson and Paulin 1995). The simulations are being used to test the role of descending signals in adaptive filtering and to explore mechanisms responsible for the learning observed in this electrosensory system. The basic circuit will next be extended into arrays of cells representing a simplified cerebellar network. In operation, the network model should learn temporal and spatial correlations within its stream of sensory and motor control inputs.

Figure 5. Principal cell model circuit from the electrosensory lobe in electric fish. (adapted from Nelson and Paulin 1995). A single principal cell receives connections from multiple sensory and descending inputs.

The circuit includes:
(1) center-surround receptive fields
(2) adaptive threshold, stochastic spiking neurons
(3) adaptive weights
(4) local anti-Hebbian synaptic learning rules
(5) the known network inputs and connectivity.

Preliminary simulation results show that this circuit can successfully learn to suppress predictable inputs arising from the fish's own motor behaviors, while remaining sensitive to external stimuli.



Our initial goals are to mimic a few well studied cerebellar subsystems – for example, the vestibulo-ocular reflex for image stabilization, or sensory prediction and compression in electric fish. Our long range goal is to combine feedforward predictive control of system dynamics (using a world model) with feedback error correction (to correct errors in the motor output and/or update the world model), in order to achieve adaptive sensory filtering and efficient, coordinated movement for autonomous biomorphic explorers. Our long-term goal is to implement these artificial cerebellar networks in silicon, incorporating: (1) the functional architecture of the cerebellum, (2) adaptive threshold spiking neurons, (3) on line Hebbian learning and adaptation, and (4) 3-D chip stacking for massive connectivity. Using the spike timing of neurons to represent information provides natural advantages in implementing local Hebbian learning of correlations. The 3-d chip stacking process may be very well suited to implement the 3-d cerebellar architecture, allowing high enough connection densities to capture its processing power. For low power consumption, we will design for subthreshold analog operation in a CMOS process. The resulting hardware should pack high computational power dedicated to sensory-motor processing into a very efficient, small, low mass, low power package.

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